HAWK: An Unmanned Mini Helicopter-based Aerial Wireless Kit for Localization

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***Abstract*—This paper presents a fully functional and highly portable mini Unmanned Aerial Vehicle (UAV) system, HAWK, for conducting aerial localization. HAWK is a programmable mini helicopter - Draganflyer X6 - armed with a wireless sniffer - Nokia N900. We developed custom PI-Control laws to implement a robust waypoint algorithm for the mini helicopter to fly a planned route. A Moore space filling curve is designed as a flight route for HAWK to survey a specific area. A set of theorems were derived to calculate the minimum Moore curve level for sensing all targets in the area with minimum flight distance. With such a flight strategy, we can confine the location of a target of interest to a small hot area. We can recursively apply the Moore curve based flight route to the hot area for a fine-grained localization of a target of interest. Therefore, HAWK does not rely on a positioning infrastructure for localization. We have conducted extensive experiments to validate the feasibility of HAWK and our theory. A demo of HAWK in autonomous fly is available at http://www.youtube.com/watch?v=ju86xnHbEq0.**

I. INTRODUCTION

In this paper, we present HAWK, which is a programmable mini unmanned helicopter armed with a wireless sniffer and is fully functional for localization tasks. HAWK is an infrastructure-free, training-free, and highly portable localization tool and is the first such tool based on an autonomous mini helicopter.

HAWK is a warflying tool. It is more accurate than a warwalking or wardriving tool [1]. Since HAWK can fly to any point in open space, we can set up an airborne Kismet [2] with GPS on HAWK and produce a fine-grained geographical map of wireless access points (APs) or routers. Wardriving and warwalking are not able to provide such location granularity since it is not possible for cars and not convenient for people to access dead ends such as building roofs.

HAWK can also be used for search, rescue, and surveillance. It is able to sense a target mobile through its wireless signals, either cellular or WiFi. For instance, modern smartphones are often equipped with WiFi devices, which send out probing signals intermittently [3]. When we search and rescue a lost traveler or a survivor from building debris after an earthquake, we can position her by localizing her active smartphones via HAWK flying slowly at a low altitude. HAWK can also fly in the vertical plane around a skyscraper to search a suspect hiding in a room and committing attacks via WiFi. The top diameter of HAWK is only 99cm and its height is 25.4cm. It can fly both outdoors and indoors and conduct stunts that common large helicopters cannot do.

The most related work to HAWK is W.A.S.P [4]. W.A.S.P is also an UAV and has the capability of wayflying. However, W.A.S.P uses a mini **airplane**. It has to maintain a relatively high speed and this limits its capability for surveillance because of the cruising speed requirement of locating an active mobile device (Refer to our Theorem 1). In contrast, HAWK can hover statically over a target and has an approximate maximum speed of 50km/h.

We developed HAWK as a generic aerial surveillance tool. Our contributions can be summarized as follows:

- We built the fully functional HAWK, a mini helicopter - Draganflyer X6 [5] - armed with a smartphone Nokia N900 [6] as the wireless sniffer. We established a simple mechanical dynamics model for Draganflyer X6, and developed customized PI-Control laws for pitch, roll and yaw maneuvers to control X6's movement. We implemented the waypoint functionality for X6 to take a planned route.
- We designed a Moore space filling curve based flight route for HAWK to survey a specific area without the help of any positioning infrastructure. To ensure that all target mobile devices are detected during flight, we derived the minimum Moore curve level that is constrained by flight velocity and target packet transmission interval. The Moore curve based flight route can also be optimized according to a digital map to avoid unoccupied areas and save power consumption for an UAV. From the surveillance flight, we can pinpoint a specific target to a small hot area. If fine grained target localization is required, we can recursively apply the space filling curve based flight strategy in the hot area.
- Our theorems formally prove that HAWK is more suitable for precise localization than W.A.S.P since W.A.S.P has to fly at a minimum speed to float in the air and it cannot take a Moore curve based route at an arbitrarily large level while HAWK can.
- We conducted both ns2 simulations and real-world experiments to validate the feasibility of HAWK for localization. Our experimental results match our theoretical analysis very well. We were able to achieve a localization accuracy of 5 meters on average.

The rest of this paper is organized as follows: In Section II, we present background knowledge on Moore Curve. Section III introduces HAWK's system structure, the basic idea of

aerial localization, issues and our solutions. Detailed analysis of localization performance is available in Section IV. We present experimental evaluation of HAWK in Section V. Section VI discusses related work. The conclusion of this paper is in Section VII.

II. Background

In this section, we briefly introduce Hilbert space filling curve and Moore curve. Hilbert curve [7], [8] is a space filling curve that visits every point in a square area or cube. To generate a 2D Hilbert curve of level n, we first divide a target square area into 4^n sub-squares. Such a subsquare is denoted as *unit square* in this paper. A line is then used to connect the center of each unit square based on two conditions: adjacency condition and nesting condition [7]. This line always starts from a corner in a grid and ends at one of the two adjacent corners. When n approaches infinity, the whole space is covered by the Hilbert curve.

Moore curve, starts and ends at the same point, is a variation of the Hilbert curve. It is generated by four half-size Hilbert curves placed end-to-end with appropriate orientations. To generate a level n 2D Moore curve, we need to generate four $(n-1)$-level 2D Hilbert curves. For instance, if a level $(n-1)$ 2D Hilbert curve has coordinates of $f_h = [\phi_h \ \varphi_h]'$, we can use the following four conversions to construct a 2D Moore curve f_m,

$$f_{m_1} = \frac{1}{2}\begin{bmatrix}1\\0\end{bmatrix} + \frac{1}{2}\begin{bmatrix}0 & -1\\1 & 0\end{bmatrix}\begin{bmatrix}\phi_h\\\varphi_h\end{bmatrix}, \quad (1)$$

$$f_{m_2} = \frac{1}{2}\begin{bmatrix}1\\1\end{bmatrix} + \frac{1}{2}\begin{bmatrix}0 & -1\\1 & 0\end{bmatrix}\begin{bmatrix}\phi_h\\\varphi_h\end{bmatrix}, \quad (2)$$

$$f_{m_3} = \frac{1}{2}\begin{bmatrix}1\\2\end{bmatrix} + \frac{1}{2}\begin{bmatrix}0 & 1\\-1 & 0\end{bmatrix}\begin{bmatrix}\phi_h\\\varphi_h\end{bmatrix}, \quad (3)$$

$$f_{m_4} = \frac{1}{2}\begin{bmatrix}1\\2\end{bmatrix} + \frac{1}{2}\begin{bmatrix}0 & 1\\-1 & 0\end{bmatrix}\begin{bmatrix}\phi_h\\\varphi_h\end{bmatrix}. \quad (4)$$

A 3D Hilbert curve is generated by dividing a cube into 8^n sub-cubes, and its construction formulas are provided in [8]. Similarly, a 3D Moore curve can be generated from a 3D Hilbert curve. The conversion process is similar to the process of generating a 2D Moore curve, except with eight conversion formulas. Figure 3 illustrates a level 3 Moore curve.

III. System

In this section, we first introduce the structure of HAWK and the basic idea of aerial localization. We then investigate challenging issues of aerial localization. At last, we introduce our solutions to these problems.

A. System Overview

Figure 1 illustrates the system architecture of HAWK. Figure 2 shows our UAV in action. There are five components in this system:

(i) *Helicopter*. The mini helicopter we choose for HAWK is Draganflyer X6, a remotely operated, unmanned, and programmable small helicopter designed to carry up to $500g$

Fig. 1. Architecture of HAWK

payload. For HAWK, we mount a wireless sniffer onto X6 to collect wireless traffic. X6 can be controlled by either a handheld controller or a program. **Because of the confidentiality contract with the manufacturer, we will not discuss X6's control protocol and interface.**

Draganflyer X6 is equipped with GPS, a flash card recording flight data, and XBee wireless transceivers. A transceiver can transmit telemetry messages to another XBee modem on the handheld controller and our software controller. X6 logs flight data including *GPS* position, time, height, and sends these data to the handheld controller or program every 100ms. Based on these data, we are able to apply control theory to maneuver X6 and implement the *waypoint* function for the helicopter to patrol along a Moore curve based route.

To control X6's movement, we can adjust three parameters, **pitch**, **roll** and **yaw**. Pitch controls forward or backward translational velocity, roll controls left or right translational velocity, and yaw controls left or right angular velocity.

Fig. 2. HAWK in Action

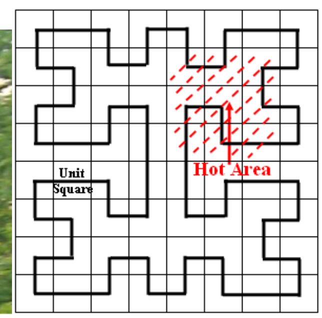

Fig. 3. Level-3 Moore Curve

(ii) *Wireless Sniffer*: We convert a smartphone Nokia N900 to a sniffer. This sniffer is attached to a tiltable mounting frame, which was designed for carrying cameras for Draganflyer X6. X6 carries the sniffer and flies over a specific region along the configured waypoints generated by a Moore curve or set through Google map via our software control interface. N900 can run Kismet identifying locations of APs.

(iii) *Handheld Controller*: This joystick controller is the master device controlling the helicopter's takeoff and landing. It also works as a remedy controller in case a software controller fails.

(iv) *Software Controller*: The software controller runs on a Lenovo W500 laptop that maneuvers the helicopter flying autonomously along a planned route. The software controller can also control takeoff and landing.

(v) *Target Device Locator*: The target device locator runs on the Lenovo W500 laptop. This locator can show X6's flight route on Google map in real time, and AP locations detected by Kismet after the surveillance flight.

B. Basic Idea of Aerial Localization

The basic idea of aerial localization via HAWK is warflying. That is, HAWK flies over a given area for a geographic surveillance of all target mobiles. For warflying, we generate a Moore curve over the target area as the flight route. To ensure all wireless devices in the area can be detected, we ought to consider the following factors: transmission range of targets, traffic model such as packet interval of targets, flight speed and level of Moore curve. If the helicopter flies too fast, targets transmit too slowly, and the level of Moore curve is too small, HAWK will miss mobile devices during flight. We control the flight very carefully so that HAWK is within target mobile devices' transmission range along the flight route. We construct the route and control the flight speed in such a way that HAWK can capture at least one packet from the target device within a unit square, as illustrated in Figure 3.

With collected target mobile RSSI (received signal strength indication) time series and coordinate information during flight, various algorithms can be applied for locating target mobiles. We adopt the one used by Kismet, which uses the location where Kismet senses the strongest RSSI as a target's location. Obviously, this is a very coarse localization strategy. Our theorems shows that this localization strategy allows us to pinpoint a specific target to nine unit squares, denoted as *hot area*, surrounding the position where the maximum RSSI is sensed, as shown in Figure 3.

For accurate localization of a particular target of interest, we design a recursive wayflying strategy. Once we have identified the hot area where a target may reside, we can repeat the warflying process on the hot area to determine a smaller and smaller hot area.

C. Issues

From the discussion above, we can see that two critical issues have to be addressed for successful aerial localization. In the rest of this section, we will address these issues.

(i) How can we implement reliable GPS based waypoints for the mini helicopter? The waypoint functionality is essential for UAV to take a specific route, such as one generated by a Moore curve. Since undetermined interference including wind may deviate the flight from the planned route, we need reliable control laws to counteract such unforeseen interference.

(ii) What factors affect localization? What level of Moore curve can ensure that all the wireless devices can be detected? Different levels of Moore curve produce different flight distance, which is constrained by the mini helicopter's battery life. What role does the flight speed play in this process? Recall that wireless packets are sent intermittently from a target wireless device.

D. Waypoints by PI Control

Mechanical Dynamics of Draganflyer X6: In order to control the helicopter, we need to derive the relationship between the input force and output velocity for pitch, roll, or yaw. Our experiments show that output velocity is approximately linear to the input value, as shown in Formulas (5), (6) and (7) respectively.

$$\begin{aligned} v_{pitch} &= 0.0036u_{pitch} - 0.0674, & (5)\\ v_{roll} &= 0.0036u_{roll} - 0.0538, & (6)\\ v_{yaw} &= 0.1808u_{yaw} - 7.996. & (7) \end{aligned}$$

We ignored the short dynamic transition process during which the helicopter reaches its static velocity, given an input force. Therefore, Formula (8) is the generalized relationship between the input force and output velocity,

$$v = a + bu, \tag{8}$$

where v is the output velocity, and u is the input value.

PI-Control Laws for Pitch, Roll and Yaw: PI control [9] is used to control the UAV flying from one waypoint to another in an appropriately straight line (route). We should take into consideration factors such as wind that may affect the helicopter's movement during the flight. We apply PI-control laws for pitch, roll and yaw to control forward or backward translational movement, left or right translational movement, and left or right spinning respectively in order to counter wind's influence.

A PI-control law can be written in (9),

$$u = -k_p e(t) - k_i \int_0^t e(t)dt, \tag{9}$$

where u is the input (pitch, roll or yaw). $e(t)$ is the error and has different meanings for pitch, roll and yaw. For pitch, it is the distance between the helicopter's current position and target position. *Great Circle Distance* [10] can be used to calculate the distance between two points on a sphere. For roll, $e(t)$ is the distance from the helicopter to the specified route (Recall the general point-line distance definition in Geometry). For yaw, $e(t)$ is the difference between helicopter's heading direction and the direction of the specific route passing the target waypoint. The integral part is the sum of $e(t)$ over time. k_p and k_i are two constants, carefully chosen to stabilize the system and control the flight velocity dynamics.

With the system state equation in (10), we can analyze the system state dynamics,

$$\dot{x} \equiv \frac{dx}{dt} = v = a + bu, \tag{10}$$

where x is the location of the helicopter, and v is the velocity (corresponding to pitch, roll, or yaw).

Stability of PI-Control: We take pitch as an example to discuss how to select k_p and k_i in (9). The analysis for roll and yaw is similar.

Our problem is to reach a waypoint quickly and smoothly along a straight flight route. Assume the waypoint is at $x = 0$, therefore,

$$e(t) = x - 0 = x. \tag{11}$$

Combine (9) and (11), and the PI-control law for pitch is given as follows,

$$u_p = -k_p x - k_i \int_0^t x dt. \tag{12}$$

Combine (10) and (12), and we have,

$$\dot{x} = -a_p - b_p k_p x - b k_i \int_0^t x dt. \quad (13)$$

Differentiate both sides of (13), and we have,

$$\ddot{x} + b_p k_p \dot{x} + b_p k_i x = 0. \quad (14)$$

The system state equation (14) is a standard second-order differential equation. There are three kinds of relationship between the two coefficients of (14) [11]: (i) When $\frac{b_p k_p}{2\sqrt{b k_i}} > 1$, the system is **overdamped**. The helicopter flies to the waypoint without oscillation, but will use more time. (ii) When $\frac{b_p k_p}{2\sqrt{b_p k_i}} = 1$, the system is **critically damped**. The helicopter flies to the waypoint as quickly as possible without oscillation. (iii) When $\frac{b k_p}{2\sqrt{b k_i}} < 1$, the system is **underdamped**. The helicopter flies to the waypoint and oscillates with the amplitude gradually decreasing to zero. In our context, we want to fly to the waypoint as quickly as possible without oscillation. Therefore, we choose $\frac{b_p k_p}{2\sqrt{b_p k_i}} = 1$.

We choose the critical damping with $\frac{b_p k_p}{2\sqrt{b_p k_i}} = 1$. If we have determined either k_p or k_i, the other can be derived. From Formula (12) and the required maximum helicopter velocity, at the start of a flight to a waypoint, with $t = 0$ and $e(t = 0)$ as the distance to the waypoint,

$$\begin{aligned} u_p &= k_p e(t = 0), & (15)\\ v_p &= a_p + b_p u_p. & (16) \end{aligned}$$

Therefore,

$$\begin{aligned} k_p &= \frac{v_p - a_p}{b_p e(t = 0)}, & (17)\\ k_i &= b_p k_p^2 / 4. & (18) \end{aligned}$$

Determining parameters for roll and yaw's PI-control laws is similar. Our software controller implements the above control laws and is able to control the helicopter flying along a specified route quickly and smoothly.

E. Moore Curve Based Flight Route

Once the functionality of waypoints is implemented, we can design various flight routes. In this paper, we use Moore space-filling curve to generate a flight route for HAWK. The goal is to ensure that we can fly the shortest distance in a given region while detecting all wireless devices. With a single channel sniffer, we attempt to detect all wireless devices active at that channel. The sniffer can also hop through all the channels to search targets, as does Kismet.

There are three reasons to use Moore curve for a planned flight route: (i) Moore curve is a space-filling curve. It passes through each point in a square (or cube) area when its level n tends to be infinite. Given the wireless device transmission range, corresponding Moore curve level and flight speed, a Moore curve based flight route can detect all wireless devices in that area. (ii) A level n Moore curve covers all unit squares with the shortest route, passing through the center of each unit square (refer to Figure 3). (iii) Moore curve begins and ends at the same point. It is practically convenient to fly the helicopter back to the takeoff position for easy retrieval.

A proper level of Moore curve is critical for reducing the total flight distance, constrained by HAWK's battery life. Our goal is to minimize the flight distance while picking up at least one wireless packet from the target wireless device in each unit square. Factors affecting the determination of the minimum level include side length d of a target area, wireless device transmission range R[1], helicopter velocity v, and wireless device packet transmission interval t. We will solve this optimization problem in Section IV.

The flight route generated above may not be optimal in practice. A Moore curve based flight route is uniformly distributed in the target area. However, we may not need to cover all the area in practice, since there may be a forest or a big lawn without any road and construction in that area. No wireless device stays there. To save battery power of Draganflyer X6, we revise the original Moore curve based flight route to follow a smarter route based on the density of population. For an area with a higher population density, we generate the Moore curve at a higher level.

The studies of economics have shown us that the road information and population density are strongly correlated. In our paper, we determine the level of Moore curve based on road information instead of population densities. The road information is retrieved from the US Census Bureau Topological Integrated Geographic Encoding and Referencing (TIGER) system, which contains information about roads for all counties in the state. Based on the information of roads, we determine whether to have more partitions of a subarea (sub-square). If the total length of a road in a sub-square is greater than a threshold, we partition this sub-square. Algorithm 1 is the smarter partition algorithm for a smarter flight route to save the helicopter's battery life.

IV. ANALYSIS

In this section, we will theoretically analyze the performance of a Moore curve generated flight route for both mini helicopter and mini airplane. We will show that since a mini airplane has to maintain a minimum flying speed, HAWK is more appropriate for warflying and accurate localization than W.A.S.P, a mini airplane based UAV.

A. Moore Curve Based Flight Route for HAWK

During the localization process, the helicopter flies along a Moore curve of a specific level. Our warflying strategy is if the target wireless device is in a unit square, the helicopter should be able to *detect* it while flying within that unit square. By detection, we mean that the helicopter captures at least one packet from the target device in the unit square. To implement this strategy, the Moore level has to be large enough.

To derive the required Moore curve level, we need Lemma 1, which gives the relationship between the transmission range

[1] In practice, the wireless device transmission range R varies with environments. We can use a worst case R or adapt R to a concrete environment.

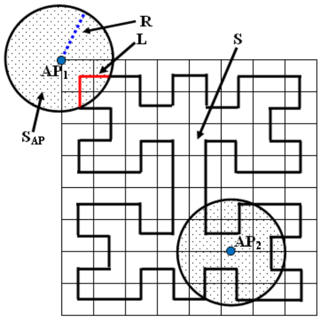

Fig. 4. Longest Consecutive Route

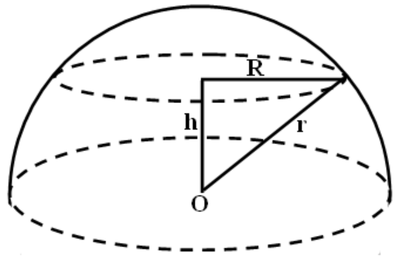

Fig. 5. Transmission Range in 3D

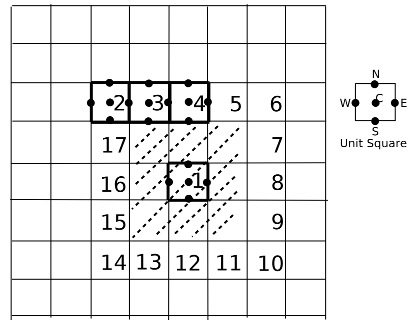

Fig. 6. Localization Accuracy Analysis

Algorithm 1 Smart Flight Route Generation

Require: Square area (A) on digital map

Set N as the level of Moore Curve
Set A.curlevel = 0
Read roads length information from digital map
function PARTITION(A)
  if total road length in $A > threshold$ **and** A.curlevel$<N$ **then**
    Partition A into 4 parts A_1, A_2, A_3, A_4
    for $i = 1, 2, 3, 4$ **do**
      A_i.curlevel $= 0$
      A_i.curlevel $=$ A.curlevel $+1$
      PARTITION(A_i)
    end for
  else
    Store the center point of A in structure P
    Store the boundaries of A in structure B
  end if
end function
Derive smart route based on P and B

of the target wireless device (and our sniffer on the helicopter) and the helicopter's speed v.

Lemma 1. *L is the length of the longest consecutive route along a Moore curve in the circular transmission range of the target wireless device. v is the helicopter maximum velocity. t is the target's minimum packet transmission interval. When*

$$L > v \times t, \tag{19}$$

the sniffer of HAWK can pick up at least one packet from the device, which can then be detected.

Please refer to our technical report [12] for the proof of Lemma 1. From Lemma 1, given a target device's transmission range and packet transmission interval, if we know L, which is shown in Figure 4, we can derive the maximum flight velocity of the helicopter. This ensures our sniffer can detect any mobile device in the target area during the surveillance.

The value L varies depending on the Moore curve level and target wireless device's position in a unit square. We determine the worst case maximum L by considering the worst case position of the target wireless device. If L can satisfy Lemma 1 in the worst case, the helicopter can detect the device in its transmission range. Lemma 2 tells us that the worst case is that a mobile device stays at vertices of the target area. Its proof can be found in our technical report [12].

Lemma 2. *If a mobile device at the vertices in the target area S can be detected, all mobile devices in S can be detected.*

To explain Lemma 2, let us see an example. In Figure 4, target AP_1 is located at a vertex of target area S, and its transmission range is S_{AP}. It is obvious that the intersected area between S_{AP} and S is the smallest compared to a target in any other positions within S.

During warflying, our helicopter flies on the horizontal plane at a certain height h above the ground. Thus, the transmission range of wireless device becomes smaller than its original value r. Lemma 3 gives the new value of the wireless device's transmission range according to the helicopter's flight height. Figure 5 shows the obvious relationship among R, h and r.

Lemma 3. *If the helicopter flies at a height h above the ground, on this horizontal plane, the target device has a new virtual transmission range R,*

$$R = \sqrt{r^2 - h^2}. \tag{20}$$

With above lemmas, we can derive a Moore curve level at which the value L satisfies Formula (19). We require that the intersection of a mobile device's transmission range and target area S includes at least one unit square and L in one unit square be great than $v \times t$ in order to guarantee that one packet is captured in that unit square. Based on Lemmas 1, 2 and 3, we can derive Theorem 1, which gives the required level of Moore curve to detect all wireless devices in a target area. Please find its proof in our technical report [12].

Theorem 1. *If all the mobile devices can be detected by HAWK, the Moore Curve level N should satisfy the following formula,*

$$\log_2 \frac{\sqrt{2}d}{R} < N < \log_2 \frac{d}{vt} \tag{21}$$

where v is the (maximum) flight speed, d is the length of the

target square area's side, R is the virtual transmission range in (20), and t is the transmission interval of the target.

In practice, since APs transmit beacon frames and mobile devices send out probing traffic regularly [3], we can easily determine t, the transmission interval of the target. For targets in fast transmission, we can pick up an appropriate t according to the preferred flight speed and distance using Formula (21).

In this paper, we use the strongest RSSI from a target to deduce the location of the target. With Theorem 1, the sniffer can capture at least one packet from a target in the target's unit square. However, the strongest RSSI may not be measured in this unit square. In Theorem 2, we identify a hot area where an interesting wireless device exists, based on the unit square with the strongest RSSI.

Theorem 2. *A target device is located in a hot area, which includes the unit square where the strongest RSSI from the target is sensed and its eight surrounding unit squares.*

To prove Theorem 2, assume the strongest RSSI is received in unit square 1 in Figure 6. We utilize an apagoge for the proof: if the target device is outside of these nine unit squares (the shaded area), the strongest RSSI can not be received in unit square 2 to 17 and beyond. For detailed proof, please refer to our technical report [12].

Once the hot area is identified, we can use a recursive approach to determine a more accurate hot area. For example, we can define a level 3 Moore curve in the hot area as new surveillance route, and determine a new velocity to satisfy Formula (21). Therefore, we can identify a smaller hot area and accurately localize a specific target.

B. Moore Curve Based Flight Route for W.A.S.P

We now formally prove the limitations of an airplane based UAV such as W.A.S.P [4] for accurate aerial localization. The Moore curve level determined in Theorem 1 ensures that there is at least one packet captured in one unit square, which means the flight velocity is upper bounded by the Moore curve level and transmission range. If this spped upper bound is greater than the minimum speed of the airplane like W.A.S.P, which has to maintain a relatively high speed to float in the air, we cannot use the warflying strategy in Section IV-A for an airplane based UAV.

To conduct an airplane based warflying, we can increase the level of Moore curve until the value L satisfies Formula (19). Theorem 3 gives the required level of Moore curve to detect all wireless devices in a target area if W.A.S.P is used for warflying. Please find its proof in our technical report [12].

Theorem 3. *For an airplane based warflying with a minimum flight speed v, the level of Moore Curve N required to detect all the mobile devices is*

$$N = n + x \tag{22}$$

where n is the smallest value satisfying the formula

$$n \geq \log_2 \frac{\sqrt{2}d}{R} \tag{23}$$

and x is the smallest positive value satisfying the formula

$$x > \log_2 \frac{2^n vt}{d} \tag{24}$$

For clarity and conciseness, we treat the area in which the wireless device can be sensed as a square inscribed in the ideal circular coverage area of the wireless device when we derive Theorem 3. Theorem 4 gives the error of this approximation.

Theorem 4. *Level N derived in Theorem 3 is at most one level greater than the smallest level needed for HAWK to detect all wireless devices in a target area.*

To prove Theorem 4, there are two situations to be considered: $x = 0$ and $x \neq 0$. In both situations, we can prove that there is no more than one level than needed. The detailed proof is in our technical report [12].

In practice, constrained by the minimum flight speed, a mini airplane cannot perform sharp turns required by a Moore curve and may not be able to fly in a small unit square determined in Theorem 3. Therefore, HAWK is more suitable for accurate aerial localization than W.A.S.P.

V. EVALUATION

In this section, we first demonstrate that our PI-control laws steer Draganflyer X6 to take a Moore curve as the flight route via field experiments on campus. The benefit of smart flight route is then presented. Since HAWK currently has a battery life for a 15-minutes flight, ns2 [13] simulations were used to validate the hot area theory in Theorem 2 and the Moore curve level selection strategy in Section IV-A. At last we will present our real-world field experimental results of accurate localization of a target wireless device.

A. PI-Control Laws for Waypoints

To test the performance of control laws steering HAWK, we conducted extensive experiments on campus. For example, we constructed a level two Moore curve as the flight route of approximate 300m. We ran Kismet on the sniffer Nokia N900 and used the handheld controller to lift the helicopter to a height of 20 meters above a building. After takeoff, the software controller autonomously controlled HAWK to fly the pre-constructed Moore curve based route. The software controller is coded according to the control laws in Section III, and the maximum flight speed is set as 2m/s. APs identified by Kismet and the flight route are drawn on Google map as shown in Figure 7. We can see that HAWK indeed took a level 2 Moore curve based route smoothly.

B. Smart Flight Route

To evaluate the advantage of smart flight route in Algorithm 1, we generate the full and smart Moore curve based flight route separately for three cities: Ware, Boxford and Lowell in Massachusetts, and compare their length.

The simulation configuration is as follows: the wireless device's transmission range is $250m$, its packet broadcasting interval is $1s$, and the helicopter's velocity is $10m/s$. Therefore, the maximum Moore curve level can be derived from

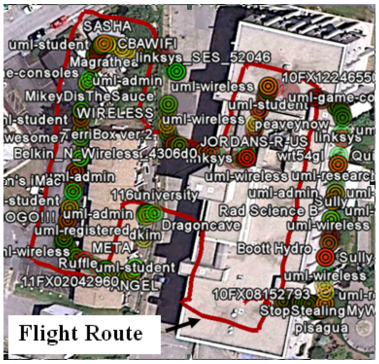

Fig. 7. 2^{th} Level Moore Curve Route

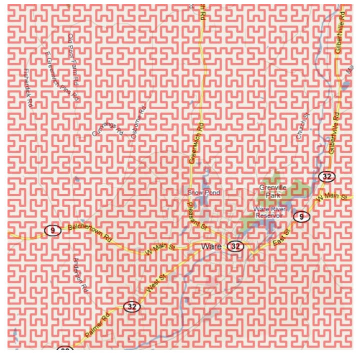

Fig. 8. Basic Route (Zigzag Lines)

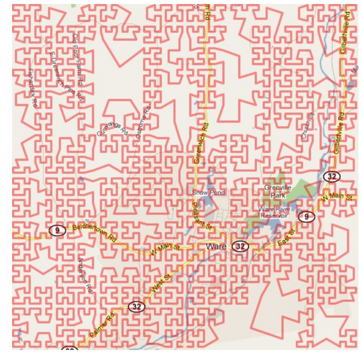

Fig. 9. Smart Route (Avoiding Unoccupied Areas)

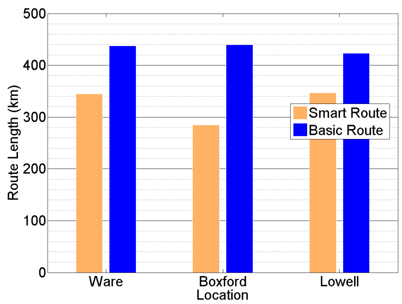

Fig. 10. Flight Route Distance Comparison

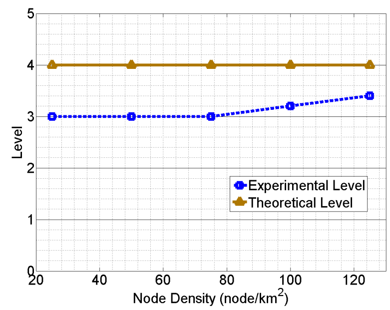

Fig. 11. Accuracy of Derived Moore Curve Level

Fig. 12. Distance Error at Different Levels

Theorem 1. Figure 8 shows the full flight route for Ware, MA on Google map, and Figure 9 is the smart flight route based on Algorithm 1, which saves around 21 percent of the full flight route. Figure 10 presents the length of the routes. It shows us that we could save approximate one third of the route length in Boxford with the smart flight route. Since the road in Ware and Lowell are denser, we save less. Therefore, the smart route may save the helicopter's battery life dramatically.

C. Analysis of Hot Area Identified by HAWK

To demonstrate the hot area theory in Theorem 2, we used ns-2 to simulate the localization process. The helicopter flies in a $2000m \times 2000m$ square area. The transmission range of the target device is $250m$, and it transmits a packet every $1s$. We used only one wireless node randomly deployed in the square area, and set five different Moore curve levels: 4, 5, 6, 7 and 8. We derived the maximum flight velocity for each level according to Formula (21).

In the simulation, the helicopter flies along the Moore curve with the velocity derived based on the Moore curve level, and we logged all distances between the wireless node and helicopter, when the helicopter received a packet from that node. We derived the minimum distance as the error of this localization. For each of the five levels and the corresponding flying velocity, we repeated the simulation 10 times. Figure 12 compares the distance error and the corresponding Moore curve level, and also shows the side width of a unit square at this level. We can observe that for each level, the distance error is less than the side width of the unit square, which verifies that the position of target device is within the hot area, including the unit square where the maximum RSSI is sensed and the surrounding eight unit squares.

D. Accuracy of Derived Moore Curve Level for W.A.S.P

To verify Theorems 3 and 4 for an **airplane** based aerial localization, we used ns-2 to simulate the localization process. In the simulation, the size of the square area and the properties of a wireless node were same as those in section V-C. However, the airplane flies at a fixed speed of 50m/s. We conducted five groups of simulations with 100, 200, 300, 400, 500 wireless nodes (target wireless devices) uniformly distributed in the area respectively. Each simulation has two steps: First, the theoretical level 4 is derived from Theorem 3; Second, we continue to reduce the theoretical level until all devices can be detected. This critical level is called *experiment level*. We run the simulation 30 times for each node density. Figure 11 compares the average experimental and theoretical level. We found that for the first three densities, the experiment level is always 1 less than the theoretical level. For the fourth density, 24 of 30 experimental level of simulations are 1 less than the theoretical level, and the experimental level is equal to the theoretical level in the other 6 simulations. For the fifth density, 18 of 30 experiment level are 1 less than theoretical level, and these two levels are equal in the other 12 simulations. These results have verified our Theorems 3 and 4. Indeed, our theorems derive a tight lower bound of Moore Curve for localization.

E. Surveillance Results Based on Kismet

We conducted real-world field experiments to evaluate the localization capability of HAWK with Kismet. Before these experiments, we generated 3 sets of Moore curve over the campus track field as helicopter's surveillance route: level 1, level 2 and level 3 Moore curves, and the warwalking route around the track field for surveillance by warwalking.

In the first experiment, we configured 12 smartphones as APs and uniformly distributed them on the track field. The Nokia N900 running Kismet was attached on the helicopter to log the locations of these 12 smartphones. Kismet was configured to hop among all the channels (default mode). The software controller on a Lenovo w500 laptop steered the flight along the three routes to locate these APs. The flight speed was upper bounded with speed calculated from Theorem 1 (t was calculated based on the beacon packet interval and the number of hopping channels). The warwalking experiment emulates the scene where people cannot access dead ends such as building roofs (the field in the experiment).

In the second experiment, all 12 APs had the same channel, Kismet was configured to sniff on this single channel, and t used for calculating flight speed was the AP's beacon transmission interval.

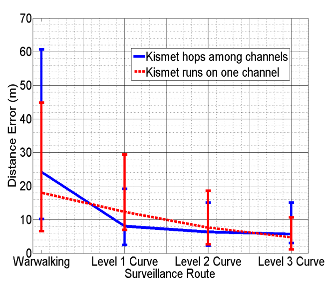

Fig. 13. Localization Error via Kismet

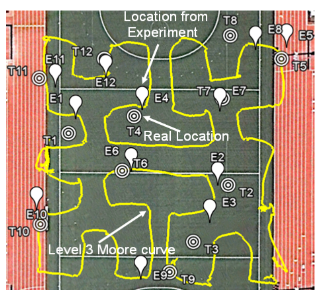

Fig. 14. APs Identified by Kismet

Figure 13 shows the accuracy of the localization are increasing when the level of flight route(Moore curve) is increased in both experiments. This validates our recursive localization strategy for fair grained localization of a target. Figure 14 shows the 12 APs' real and estimated locations with a level Moore curve 3 flight route over the track field. We can achieve an accuracy of 5 meters on average in this case.

VI. Related Work

There has been considerable amount of work on device positioning in WiFi and sensor networks. Due to space limitation, we only review most related and recent work.

W.A.S.P [4] is a mini **airplane** based UAV for warflyng. It has to maintain a relatively high speed, which limits its capability for surveillance. In [14] a mini helicopter is proposed for geographic surveillance of non wireless objects. It relies on pictures, taken by onboard cameras, to identify people and estimate their position. In [15], a space-filling curve is used as a searching route to detect mines by using swarms of mobile robots. The authors calculate the level of search route based on the sensor range and the target area. For HAWK, we generate the level based on flight velocity and target packet transmission interval as well as wireless transmission range in order to guarantee that all the wireless devices in the search region can be detected. In [16], the authors use multiple UAVs to conduct surveillance based on the uncertainty map of an unknown region. It mainly focuses on developing algorithms for optimal searching path generation, and does not consider UAV flight speed and sensing capabilities. For HAWK, we use a Moore curve as our UAV's flight route, and also design a smart route based on information of road density from a digital map.

In [17], [18], the authors proposed *SensorFly*, an aerial sensor network, where very small helicopter can self-locate itself using anchor nodes. The authors in [19] utilized biologically inspired rules of group behavior (flocking) to enable a group of UAVs to control its own motion. This project aimed at building an indoor flocking system using small co-axial rotor helicopters. Each of the swarm members is fitted with an onboard computer and a miniature wireless video camera, so that they can gather multiple views in a single pass and analyze them. Another project *SensorFlock* [20] utilizes a group of micro aerial vehicles (MAVs) for atmospheric sensing. This system requires human interaction in flight control and path planning, and it supports wireless communication networking between MAVs. In [21] the authors present *3DLoc* which is a ground based system for locating an 802.11-compliant mobile device in a three dimensional space. However, the portability and flexibility of the system is very limited and it cannot search targets in high buildings.

In [22], the authors use electronically steerable Phocus Array antennas from Fidelity Comtech [23] for wardriving and collecting RSSIs with directional information. Multiple measurements are taken from different positions and arrows are drawn toward the direction of the AP. Therefore, an AP is in the position where all the arrows are pointing to. In [24], the authors take RSSIs from wardriving and use the gradient information derived from RSSIs to infer the position of an AP. An AP is in the direction along where RSSIs increases most and the direction is represented by an arrow. Then the AP is in the position where all arrows point to. In [25], the authors built an AP equipped with a rotating directional antenna that broadcasts its direction in beacon frames. Such an AP is denoted as a directional beaconing access point (DBAP). Therefore, a mobile may position itself by using the angle of emission information from multiple DBAPs and the area intersection approach similar to those used in [26].

Some recent work recognizes the importance of 3D positioning and provides such capability [27], [28]. Nonetheless, these techniques require either the pre-installation of a positioning infrastructure (e.g., pervasive RFID tags [27]), or extensive training on the signal strength of surrounding base stations at different locations [28]. These strategies are not practical for WiFi in urban environments since the associated high cost of periodical training due to environment and infras-

tructure change and the requirement of locating a suspect in real time (i.e., it will be hard to install the infrastructure or perform training on a crime scene).

Rallapalli *et al*. [29] utilized the temporal stability and low-rank structure in mobility traces and proposed localization schemes using anchor nodes, RSSIs and hop-count information in sensor networks. *EZ localization* [30] is a WiFi-based configuration-free indoor localization method consisting of a localization server which estimates the absolute coordinate of a mobile device given its RSSIs from visible WiFi APs and its GPS positions occasionally obtaind at the entrance of a building or near a window. [31] proposed SISR, an error-tolerant localization method for wireless nodes that employ RF ranging in an outdoor, open-space environment. The authors in [32] proposed *SurroundSense*, a mobile phone based system which constructs identifiable fingerprint for a logical localization.

VII. Conclusion

This paper presented HAWK, an infrastructure free and highly portable system for aerial localization of wireless devices in a 3D space. We developed a software controller that utilizes PI-control laws to implement a robust waypoints functionality. For warflying, we generate a Moore curve over the target area as the flight route. To ensure all wireless devices in the area can be detected, we considered the following factors: transmission range of targets, traffic model such as packet interval of targets, flight speed and level of Moore curve, and developed a set of theorems. A minimum Moore curve level is carefully selected so that all wireless devices can be detected at a minimum flight distance. Our theorems ensure that the target device is pinpointed to a small hot area during one fly. A recursive wayflying process over the hot area can refine the accuracy of localization. We conducted extensive ns2 and real world experiments. The experimental results match the theorems very well. We are able to achieve a localization accuracy of 5 meters on average.

Our future work includes the study of aerial localization of targets with complicated traffic models and the use of a swarm of UAVs for collaborative localization. For example, three UAVs can work as anchor nodes high above in the sky. They provide a positioning service via laser or sonar to a fourth UAV to locate a target in areas where GPS signals are blocked.

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